DESIGN AND DEVELOPMENT OF A GENERIC FRAMEWORK FOR SURFACE WATER DELINEATION AND MONITORING USING A HYBRID LEVEL SET ALGORITHM ON LANDSAT MULTI-SPECTRAL DATA

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DOCTOR OF PHILOSOPHY

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CONTENTS

ABSTRACT

1 INTRODUCTION 1

2 LITERATURE REVIEW 4

3 PROBLEM IDENTIFICTION & STATEMENT 6

4 OBJECTIVES & METHODOLOGIES 7

5 RESUTS & DISCUSSIONS 14

6 CONCLUSION AND FUTURE WORK 27

BIBLIOGRAPHY 28

PUBLICATIONS AND PROCEEDINGS 30

ABSTRACT

Surface water bodies are critical to the existence and sustenance of civilizations. Water bodies in urban cities across the world have undergone drastic decline in quality and quantity. This has been the result of a multitude of reasons like increase in population, urbanization and encroachment. Monitoring changes to water bodies is a necessary requirement in devising strategies to conserve them. This research proposes a generic framework for monitoring and forecasting changes in the surface area of lakes using a hybrid level set algorithm for water body delineation followed by a double exponential smoothing model for forecasting. The proposed hybrid level set algorithm combines the advantages of edge based and region based level sets. An edge detection term is introduced into the formulation which improves the delineation accuracy by forcing the level set evolution to stop at the boundaries of the region of interest. The performance of the algorithm was analyzed using Pearson's Correlation Co-efficient (PCC), Structural Similarity Index (SSIM) and DICE Similarity index and found to have superior performance compared to established methods in the literature. The study uses Landsat multi-spectral data for the last 30 years to build the proposed framework for forecasting the changes in the surface area of water bodies. The experiments were conducted for nine lakes in Bangalore, a fast growing city in India, and a steady decrease in the surface area is observed for most of the lakes that were studied. The city's renovation attempts have also seen that the some of the lakes are sustaining the rapid urbanization. The proposed forecast model has yielded acceptable results with an average error of 0.072 and a correlation coefficient of 0.94 between the actual surface area and the forecasted surface area. The framework can be customized in the future to study specific water bodies by plugging in external parameters to improve the forecasting accuracy.

1. INTRODUCTION

Surface water bodies play a vital role in ground water recharge in addition to being the direct source of water to animals and plants around it. They also help in mitigating flood and its after effects especially in highly urbanized cities. Over the past few decades, the world has witnessed a drastic depletion in the quantity of water in its surface water bodies. Detecting and monitoring temporal changes to the water bodies using remote sensing images has been attempted by researchers with a lot of success. Water delineation has been performed predominantly using spectral index based and machine learning based techniques using multi-spectral images from different earth observing satellites. Most common satellites acquiring and delivering multi-spectral images are Landsat series Moderate Resolution Imaging Spectro-radiometer (MODIS), SPOT Satellite for observation of Earth , Gaofen series, Hyperion, Sentinel, QuickBird, World View and LISS [1]. As satellite images are available for any location of the earth, even for the past years, a forecasting model can be developed to estimate and visualize the expected changes to the water body and necessary measures could be employed accordingly. Landsat multi-temporal data has been used widely for change detection studies on various land cover classes [2,3,4]. Spectral indices like Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index NDWI and Modified Normalized Difference Water Index MNDWI are effectively used on these remotely sensed multi-spectral images to detect and monitor changes to water bodies [5,6]. The main steps involved in building a change forecasting model are identifying and acquiring the appropriate dataset, applying the most suitable water delineation and quantification method on the acquired multi-temporal data and building an effective forecasting model using the time-series data. Exponential smoothing based forecasting is proven to be effective in forecasting lake area changes over a period of time [7]. As the parameters affecting the lake surface area are numerous and varies according to specific lakes, it is infeasible to develop parametric forecasting model for lake area. Thus generic models for forecasting are developed solely from the past data for the lake and do not consider external parameters related to climate and population.

This research proposes a lake area change monitoring and forecasting framework that could be applied to any water body with available multi-temporal data. Landsat 5 and Landsat 8 time-series data are used in combination with MNDWI and a hybrid level-set based water delineation algorithm to detect and segment out the lake from the background. A double exponential smoothing model is then used to forecast the surface area of the lake from the past data without

considering any of the external parameters. Exponential smoothing is a proven forecasting method for univariate time-series data. The accuracy of the model was validated by computing the average error and correlation co-efficient between the actual surface area and the forecasted surface area.

Water exhibits a very distinct spectral behavior in the Electro Magnetic spectrum, called spectral signature. The spectral signature for water is presented Fig 1 which justifies the use of NIR and SWIR bands in water related studies using remote sensing images. The reflectance is negligible for water in NIR band and beyond which means that water bodies will appear very dark or black if images are captured at these bands. Most of the earth observing satellites capture images in these bands owing to their aforementioned importance in water related studies.

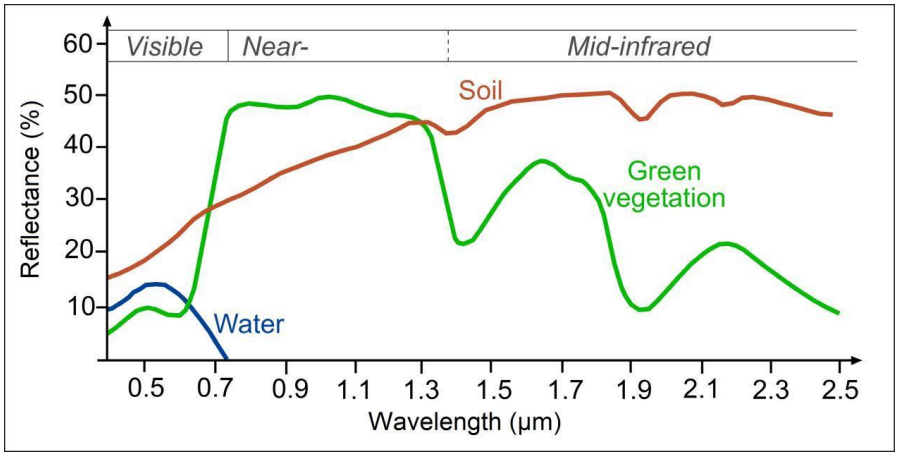

Fig 1: Spectral signature of water [Lillesand et al. (2015)]

Monitoring the water bodies for the changes happening to them manually is a very time consuming and costly task. This work proposes to develop a generic framework that can be used to monitor and forecast the changes happening to water bodies in terms of surface area by applying a hybrid level set delineation algorithm and double exponential smoothing forecasting on Landsat images. Such a framework would considerably reduce the cost and time taken to monitor and analyze the temporal and seasonal changes to the water bodies.

This study is particularly relevant for Indian cities because due to the innumerable factors like increase in population, industrialization, increase in vehicles and construction works, our natural resources are getting neglected. This negligence has led to a drastic decrease in the quantity and the quality of our natural resources like water. This study can provide a comprehensive analysis of the changes that has happened to our natural resources over the years in terms quantity and help

the concerned people take necessary actions to preserve our natural resources. Clean water and sanitation (SDG 6) is one of the Sustainable Development Goals set by United Nations Member States in 2015 to provide a shared plan for peace and prosperity for people and the planet. This study maps perfectly to this SDG and can help in ensuring the availability of clean water by conserving surface water. This research also maps to SDG 11, sustainable cities and communities, as conserving water bodies directly impacts the sustainability of cities. The proposed framework could be effectively used to monitor and forecast the changes in water bodies thereby devising better strategies to conserve them for the future.

2. LITERATURE REVIEW

Water body change detection studies are critical to study the temporal and seasonal changes to water bodies. Surface water detection and delineation is the first step in developing a change detection model. The most widely adopted water delineation methods are those based on spectral index and those based on machine learning. This research proposes to develop generic change detection framework by adopting a hybrid level set based segmentation on Landsat multispectral images. Despite the fact that level set based segmentation is commonly utilised in many image processing applications, it is yet to be thoroughly evaluated in remote sensing applications. On high resolution TerraSAR-X data, Thomas Hahmann and Birgit Wessel (2010) developed a semi-automated water body recognition approach employing active contours [8]. Y.H. Dandawate and Sneha Kinlekar (2013) used the modified Chan-Vesse method to detect rivers and coastlines [9] and they used Landsat 7 data for their study. Jun Pan and Mi Wang (2016) developed an enhanced seeded region growth algorithm for detecting water bodies from areal image data [10]. Chuan Xu, Haigang Sui, and Feng Xu (2016) used a visual saliency model and multi-scale level sets on Synthetic Aperture Radar data to build a land surface water mapping approach [11]. Meng, Q (2019) proposed another level set based approach for water detection using (Synthetic Aperture Radar) SAR data and factorization based active contours [12]. To detect water body changes using Landsat 7 data, Zhang, Xiaokang (2017) used levels sets together with an enhanced (Markov Random Field) MRF [13]. On the basis of Landsat 8 data, Zhang Mei-mei (2018) developed an automated glacial lake mapping approach based on non-local active contours [14]. Fig 2 summarizes various commonly adopted methods for surface water detection from remote sensing images and Table 1 summarizes the commonly used remote sensing data for such studies.

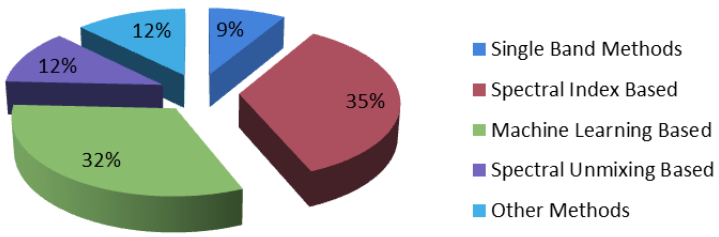

Fig 2: Categorization of commonly used water detection methods

Table 1: Categorization of commonly used water detection methods

Satellite/sensor	No. of EM bands [Bands]	Spatial resolution (m)
Landat MSS	4 [G,R,NIR1,NIR2]	60 m
Landsat TM	7 [B,G,R, NIR, SWIR1,Thermal,SWIR2]	30 m
Landsat ETM+	8 [B,G,R,NIR, SWIR1,Thermal,SWIR2,PAN]	30 m (PAN—15 m)
Landsat 8 OLI	11 [Bands in ETM+ and Ultra Blue, Cirrus]	30 m (PAN—15 m)
Suomi NPP-VIIRS	22 [640–12010 nm]	375 m (1–5), 750 m (6–22)
MODIS	36 [620–14385 nm]	250 m (1–2), 500 m (3–7), 1000 m (8–36)
SPOT 4	5 [Green, Red, NIR, SWIR, Monospectral]	20 m (Monospectral—10 m)
SPOT 5	5 [Green, Red, NIR, SWIR, Panchromatic]	10 m (PAN—5 m/2.5 m)
EO-1 ALI	10 [48–2350 nm]	30 m (PAN—10 m)
GF01 and GF02	5 [450–890 nm]	8 m (PAN—2 m)
Hyperion data	220 [357–2576 nm]	30 m
Sentinel-2 MSI	13 [444–2204 nm]	60 m(1, 9 & 10),10 m (2–4 & 8), 20 m(5–8a, 11–12)
QuickBird	5 [450–900 nm]	2.62 m (PAN—65 cm)
World View 2	9 [400–1040 nm]	2.07 m (PAN—0.52 m)
LISS IV	3 [520–860 nm]	5.8 m
MERIS	15 [390–1040 nm]	Ocean: 1040 × 1200 m, Land: 260 × 300 m
MUX/CBERS-4	4 [450–890 nm]	20 m

This research proposes to implement a hybrid level set algorithm on Landsat multi-spectral data to produce an effective surface water delineation approach that can be used to automate change detection studies. The existing algorithms for water delineation using level sets are implemented either by considering the local features of the image of the global features. To achieve better segmentation results, the presented approach takes into account local and global image attributes, and appropriate preprocessing techniques are introduced, making the algorithm resilient and effective on multi-temporal data.

3. PROBLEM IDENTIFICATION AND STATEMENT

Surface water is one of the important natural resources that has been depleting in an alarming rate over the past few years. It is critical to understand the pace and manner in which this depletion has been happening to the surface water bodies. It is also important to understand the seasonal dynamics of the water bodies to device strategies for the better utilization of these resources. With the availability of multi-spectral satellite images, it is now possible to develop algorithms that can automatically detect and delineate surface water bodies and model the temporal changes happening to them at a relatively lower cost and in much lesser time. Digital image processing techniques can be employed to extract the otherwise hidden information in remote sensing images and analyzed to make useful inferences and consequently to take more informed decisions. This study aims at designing and developing a generic framework to accurately detect and delineate surface water bodies and to monitor and forecast the temporal changes in surface area. The problem statement for this research work is formulated as "*Design and Development of a Generic Framework for Surface Water Delineation and Monitoring Using a Hybrid Level Set Algorithm on Landsat Multi-spectral Data*".

4. OBJECTIVES AND METHODOLOGIES

The objectives of the proposed study are

1. To analyse existing water delineation methods to identify the most suitable method and the most suitable data for the study and also to develop an effective pre-processing algorithm for the chosen Landsat data.
2. To develop an improved water delineation algorithm using level set theory on Landsat multispectral images.
3. To develop a generic framework by extending the improved water delineation algorithm to multi-temporal Landsat data to monitor and forecast changes in water bodies.

4.1 Methodology

This study aims at designing and developing a generic framework for surface water delineation and forecasting using a hybrid level set algorithm on Landsat multi-spectral, multi-temporal data. The methodology followed is depicted in Fig 3.

4.1.1 Multispectral Data

This research has used multi-spectral images from the Landsat 5 and Landsat 8 repository in U.S.Geological Survey portal. All the spectral bands are acquired at spatial resolution of 30 meters except the Panchromatic band in Landsat 8, which has 15 meters spatial resolution Table 2 presents the bandwidth and spatial resolution of all the Landsat 5 and 8 spectral bands. [15].

Table 2: Landsat Multispectral Image Bands and details

	Landsat 5		Landsat 8	
Bands	**Wavelength (micrometers)**	**Resolution (meters)**	**Wavelength (micrometers)**	**Resolution (meters)**
B1	Blue (0.45 - 0.52)	30	Ultra Blue (0.435 - 0.451)	30
B2	Green (0.52 - 0.60)	30	Blue(0.452 - 0.512)	30
B3	Red (0.63 - 0.69)	30	Green(0.533 - 0.590)	30
B4	NIR (0.77 - 0.90)	30	Red(0.636 - 0.673)	30
B5	SWIR1 (1.55 - 1.75)	30	NIR(0.851 - 0.879)	30
B6	TIR (10.40 - 12.50)	30	SWIR1(1.566 - 1.651)	30
B7	SWIR2 (2.09 - 2.35)	30	SWIR2(2.107 - 2.294)	30
B8	Not Applicable		PAN(0.503 - 0.676)	15
B9	Not Applicable		Cirrus(1.363 - 1.384)	30
B10	Not Applicable		TIRS1(10.60 - 11.19)	100 * (30)
B11	Not Applicable		TIRS2(11.50 - 12.51)	100 * (30)

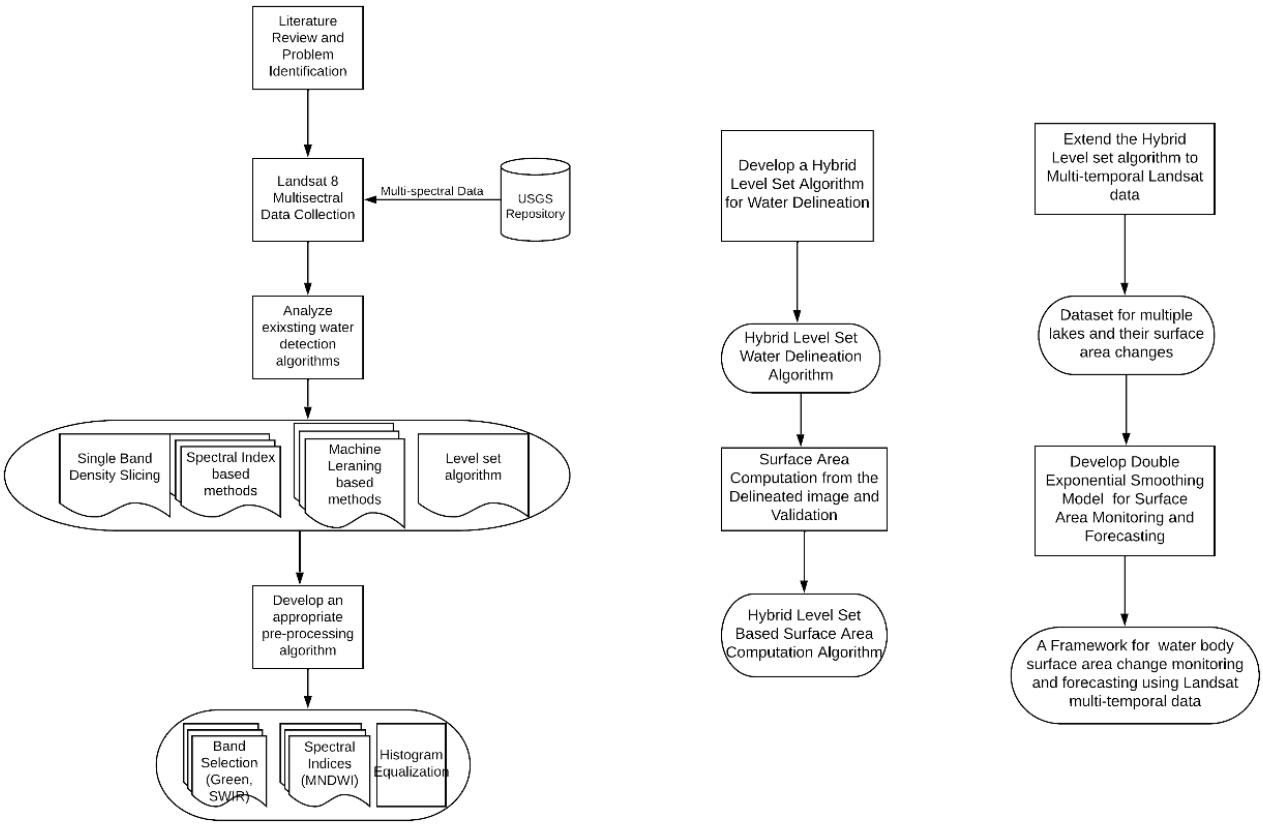
Literature Review and Problem Identification
Landsat 8 Multisectral Data Collection
Multi-spectral Data
USGS Repository
Analyze exixsting water detection algorithms
Single Band Density Slicing
Spectral Index based methods
Machine Leraning based methods
Level set algorithm
Develop an appropriate pre-processing algorithm
Band Selection (Green, SWIR)
Spectral Indices (MNDWI)
Histogram Equalization
Develop a Hybrid Level Set Algorithm for Water Delineation
Hybrid Level Set Water Delineation Algorithm
Surface Area Computation from the Delineated image and Validation
Hybrid Level Set Based Surface Area Computation Algorithm
Extend the Hybrid Level set algorithm to Multi-temporal Landsat data
Dataset for multiple lakes and their surface area changes
Develop Double Exponential Smoothing Model for Surface Area Monitoring and Forecasting
A Framework for water body surface area change monitoring and forecasting using Landsat multi-temporal data

Fig 3: Methodology Flow diagram

4.1.2 Pre-processing Algorithm

Existing water delineation methods like spectral indices and machine learning based techniques are analyzed and evaluated to understand the gaps and scope in developing a level set based water delineation algorithm. The need for an effective pre-processing algorithm was identified to address issues of dimensionality reduction, normalization and image enhancement. Modified Normalized Spectral Index was found to be effective in normalizing the pixel values to a common range and was used along with histogram equalization to proposes an effective pre-processing algorithm. The algorithm is presented in the Algorithm 1.

Algorithm 1 Algorithm for Pre-processing the Landsat Multi-spectral Image

Input: Landsat 5/ Landsat 8 Multi-spectral Image
Output: Pre-processed image that can be input for the Hybrid Level Set Algorithm

1: Read the Landsat 5/ Landsat 8 Multi-spectral Image
2: **if** Input image is Landsat 5 **then**
3: $Green$ = BAND2
4: $SWIR$ = BAND5
5: **end if**
6: **if** Input image is Landsat 8 **then**
7: $Green$ = BAND3
8: $SWIR$ = BAND6
9: **end if**
10: Compute the Spectral Index MNDWI (Modified Normalized Difference Water Index) as

$$MNDWI = \frac{Green - SWIR}{Green + SWIR}$$

11: Perform Histogram Equalization on the MNDWI Image

4.1.3 A hybrid level set based water delineation algorithm

A level set is an implicit representation of a curve. In level set based segmentation, an initial level set curve is arbitrarily fixed on the image and then evolved according to force function. Usually the force that controls the level set evolution is the curvature of the level set function, which is a geometric property of the function. An additional term is introduced in the hybrid level set formulation called edge stopping function for forcing the level set evolution to stop at object boundaries. This function can be built as a function of the image gradient. The initial level set, also known as the initial contour C0, is randomly placed on the image and evolves over time using a force function until it satisfies a stop condition. The level set evolution force is typically a feature of the image, such as image gradient.

Consider a level set function ϕ(x,y,t); where t is a time variable added to allow the level set to evolve over time. The level set curve's continuous evolution is governed by equation (1).

$$\frac{\partial \phi}{\partial t} = F\left|\nabla \phi\right| \tag{1}$$

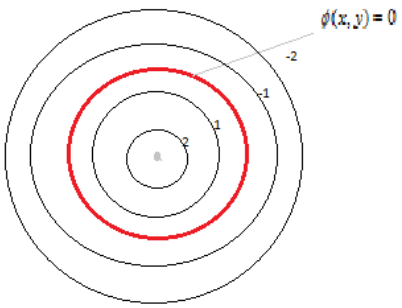

Fig 4: A Level Set Function

Fig 4 presents a sample level set function and the function φ(x,y) = 0 corresponds to the initial contour C_0. The force F acts perpendicular to the direction of level set. Generally, in a level set model, the driving force F is the curvature of the level set curve as given in equation (2).

$$F = \frac{\phi_y^2 \phi_{xx} - 2\phi_x \phi_y \phi_{xy} + \phi_x^2 \phi_{yy}}{\left(\phi_x^2 + \phi_y^2\right)^{3/2}} \tag{2}$$

∇φ is the gradient of the level set function φ(x,y,t).

4.1.3.1 Image segmentation using level sets

Image segmentation deals with separating the background from the regions of interest for further processing. Image segmentation can be performed using level sets by introducing an edge stopping function to the basic level set formulation. The partial differential equation incorporating the edge stopping function is given in equation (3).

$$\frac{\partial \phi}{\partial t} = g(x,y) F |\nabla \phi| \tag{3}$$

The function $g(x,y) = 1 / \left(1 + |\nabla f|^2\right)$, where f is the image, is called the edge stopping function.

Because the image gradient is comparatively stronger at the object boundaries, the value of this function approaches zero at the object boundaries. As a result, the edge stopping function at the boundaries becomes zero, and the level set evolution comes to a halt at the object boundary. The level set evolution stops at the image boundaries as illustrated in Fig 5.

Fig 5: Level Set Evolution

Two commonly employed models for level set based boundary segmentation are edge-based and region-based models. Edge-based methods usually depend on the measures of intensity variations at the edges like the gradient or other partial derivatives. Segmentation accuracy using edge-based models depend predominantly on the initial position and size of the level set and also are sensitive to noise and other image deteriorations. Region-based models operate by partitioning the image into objects and background depending on pixel intensity similarity. Region-based models use statistical information of the pixels inside and outside the contour to govern the evolution. This

makes it less noise-sensitive and gives better performance on weak-edge and edge-free images. This method is not dependent on the position and size of the initial contour and is therefore said to possess the property of global segmentation.

This work presents a hybrid level set model which uses both edge based and region based models to improve the accuracy of segmentation. The proposed PDE formulation is an ensemble of region based models and edge-based models thus harnessing the advantages of both the models. The force functional to be optimized in-order to evolve the level set function to surround the object to be segmented is given in equation (4).

$$F(c_1, c_2, \phi) = \mu.length(\phi) + \lambda \int_{inside(C)} |u_0 - c_1|^2 dxdy + \lambda \int_{outside(C)} |u_0 - c_2|^2 dxdy + \int g(x, y) dxdy \qquad (4)$$

where c_1 and c_2 are the average pixel intensities of u_0 inside and outside the contour C respectively and μ and λ are weights. The length of the curve is added as a regularization term and the subsequent two terms represent the region based energy and the last term is the edge stopping function. The length of the level set curve is replaced with the corresponding integral to get equation (5).

$$F(c_1, c_2, \phi) = \mu \int \delta(\phi(x, y)) |\nabla \phi(x, y)| dxdy + \lambda \int_{inside(C)} |u_0 - c_1|^2 dxdy + \lambda \int_{outside(C)} |u_0 - c_2|^2 dxdy + \int g(x, y) dxdy \qquad (5)$$

The function δ (ϕ) is called the Dirac delta function of the Heaviside function H that is used to initialize the level set function. Heaviside function and the Dirac delta function are defined in equation (6) and (7) respectively.

$$H(z) = \begin{cases} 1, if \ z \geq 0 \\ 0, if \ z < 0 \end{cases} \qquad (6)$$

$$\delta(z) = \frac{d}{dz} H(z) \qquad (7)$$

The force functional presented in equation (5) can be minimized by constructing corresponding PDE. The resulting Euler-Lagrangian equation for the force functional keeping c_1 and c_2 constant is presented in equation (8).

$$\frac{\partial \phi}{\partial t} = \mu \delta(\phi) div\left(\frac{\nabla \phi}{|\nabla \phi|}\right) + \lambda (u_0 - c_1)^2 + \lambda (u_0 - c_2)^2 + 1 \Big/ \left(1 + |\nabla f|^2\right) \qquad (8)$$

The terms μ and λ are to be carefully tuned depending on the smoothness and texture characteristics of the image and div is the divergence operator. This formulation is based on the works of Tony Chan (2001) and Xavier Bresson (2007) (2009) [16,17,18]. After applying the

hybrid level set based water delineation, surface area is computed as per the formula given in Algorithm 2.

Algorithm 2 Hybrid Level Set Water Delineation Algorithm

Input: Pre-processed Landsat image of the desired water body

Output: Segmented Image of the Water Body and the Surface Area in square kilometers

Initialisation : Initialize the level set function ϕ using eq. 7

1: Read the pre-processed image and Compute the initial level set function
2: **while** *Convergence condition is not met* **do**
3: Update the level set function ϕ using the PDE in Eq.8
4: Fine tune the parameters μ and λ
5: **end while**
6: Remove the level set curves whose length is smaller than a threshold value (depending on the size of the water body under study) to remove unwanted water bodies
7: Binarize the image by converting water pixels to 255 and non-water pixels to 0
8: Compute the surface area of the water body as $SurfaceArea$ = Number of White Pixels * 900 / 10^6

return $SurfaceArea$

4.1.4 Double Exponential Smoothing Based Forecasting

Exponential smoothing is a popular technique used in forecasting univariate time-series data which uses the weighted averaging to smooth the data and do the forecasting. This is similar to Autoregressive Integrated Moving Average (ARIMA) family of models for forecasting univariate time-series data, which uses weighted linear sum of previous data in the series. In exponential smoothing, the weights are decremented exponentially as we move further back in time, ensuring more weightage for recent data. Two most commonly used variants of exponential smoothing models are Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES). Single exponential smoothing does not take the trend factor into account while smoothing the data. SES formulation has only a single parameter alpha, called the smoothing factor. The value of this parameter determines the rate at which the weight of previous data points decrement exponentially. Equation (9) shows the formulation of the single exponential smoothing model.

$$\hat{y}_x = \alpha . y_x + (1-\alpha) . \hat{y}_{x-1} \tag{9}$$

Where, $\hat{y}_x$ is the forecasted value of y, also called the level and α is the smoothing factor. α takes values between 0 and 1 and a value close to 1 gives high weightage to the recent observations. As opposed to single exponential smoothing, double exponential smoothing takes the trend in the data into account and thus requires two parameters α and γ. In addition to the smoothing factor, an additional parameter called trend or slope (γ) is added to the formulation to account for the trend on the time-series data. A double exponential smoothing model is referred to as a linear trend model or exponential trend model based on whether the trend is additive or multiplicative. The additive trend model is used in this work and the formulation is given in Equation (10), (11) and (12).

$$l_x = \alpha.y_x + (1-\alpha).(l_{x-1} - b_{x-1}) \tag{10}$$

$$b_x = \gamma.(l_x - l_{x-1}) + (1-\gamma)b_{x-1} \tag{11}$$

$$\hat{y}_{x+1} = l_x + b_x \tag{12}$$

$\hat{y}_{x+1}$ is the forecasted value, b_x is the trend or the slope and l_x is the level.

The proposed generic framework will take multi-temporal Landsat data as input and can be used to monitor the changes in surface area of water bodies of interest. It can also be used to forecast the expected surface area in the coming years so that the authorities concerned can devise strategies to conserve the water bodies. The proposed framework is presented in Fig 6.

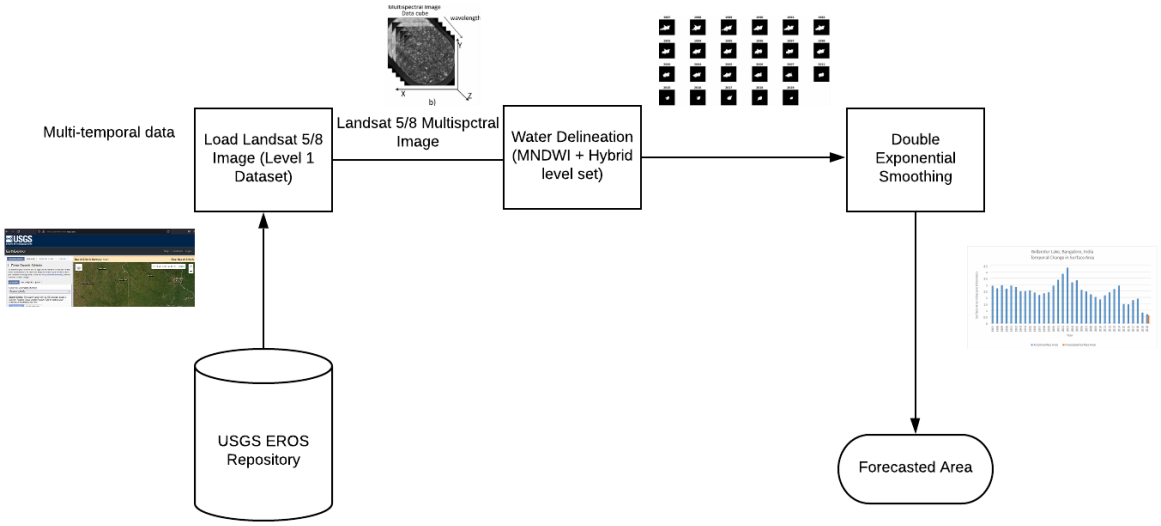
Multi-temporal data
Load Landsat 5/8 Image (Level 1 Dataset)
Landsat 5/8 Multispctral Image
Water Delineation (MNDWI + Hybrid level set)
Double Exponential Smoothing
USGS EROS Repository
Forecasted Area

Fig 6: Proposed generic framework for surface water delineation and change forecasting

5. RESULTS AND DISCUSSION

The results pertaining to the objectives of this study is presented along with detailed discussion in this section. All the experiments are conducted on a laptop with quad core processor and 8 GB RAM using MATLAB. An effective pre-processing algorithm was presented in the previous section which was developed for performing dimensionality reduction, normalization and enhancement of the Landsat data obtained from the USGS portal. Fig 7 shows the important bands in the Landsat multi-spectral image and Fig 8 presents the effect of pre-processing on the data.

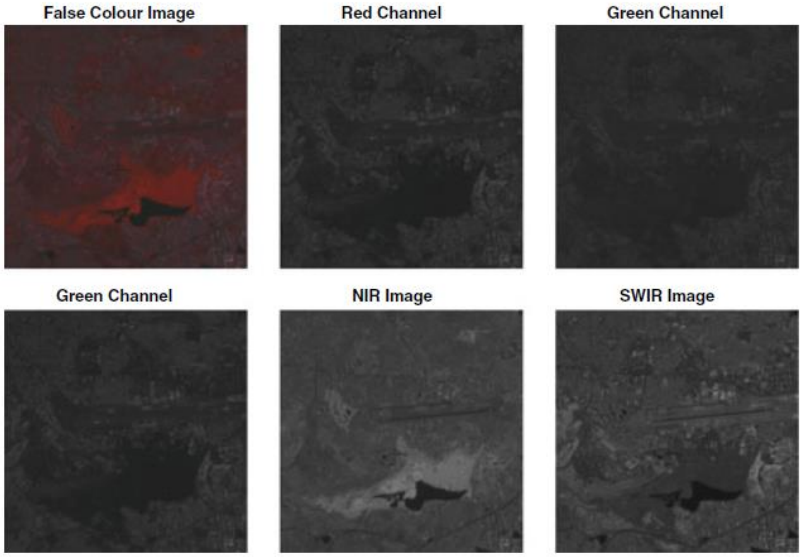

Fig 7: Sample Landsat data with important bands for the study

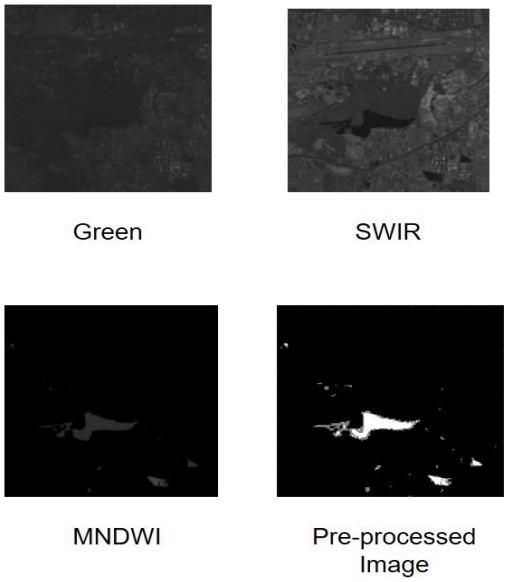

Fig 8: Sample Landsat data with important bands for the study

A hybrid level set algorithm was developed as per the mathematical model discussed in the previous section and the algorithm was tested with Landsat images of various lakes with surface area ranging from 0.5 km^2 to 300 km^2 approximately. The algorithm was also tested on multi-temporal images to evaluate its effectiveness in carrying out change detection studies. This phase of the research focused on developing an image processing based water body change detection method using Landsat multispectral images over the past 25 years. Water bodies are delineated from multispectral images using the developed hybrid level set based segmentation technique. The surface area of the identified water bodies is then calculated, and an exponential smoothing model is employed to forecast future change based on prior data. The outputs in Figures 9 and 10 demonstrate the efficiency of the hybrid level set in delineating water bodies from Landsat images.

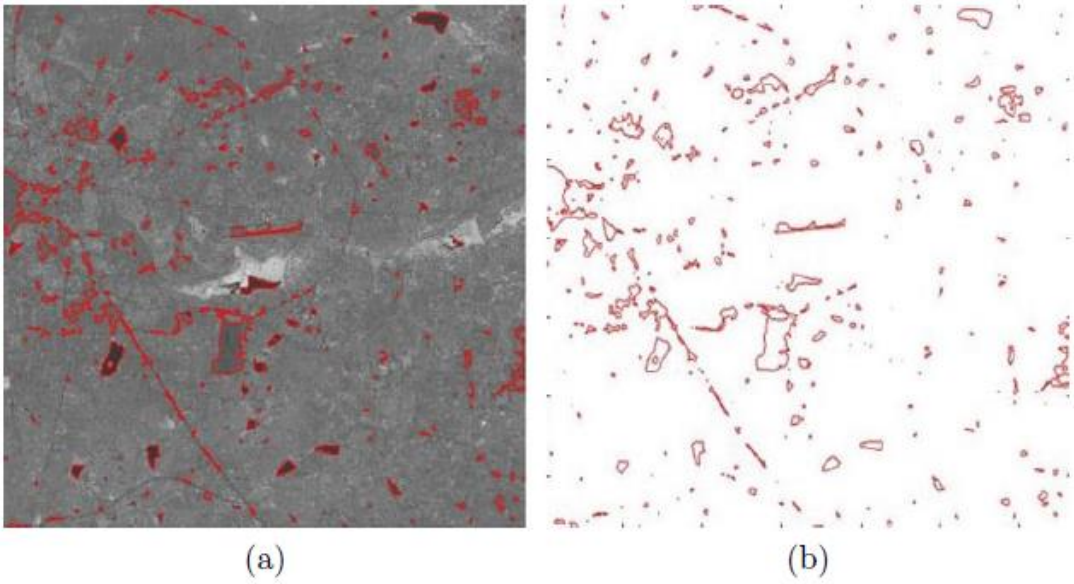

Fig 9: Sample delineation output. (a) Level set super imposed on NIR band (b) Level set output

Fig 10: Delineation output for a selected water body (NIR image, Level set image and binary image with water pixels as white and non-water pixels as black.

Fig 11 shows how the delineation results varied with respect to the weight parameters μ and λ. The values for the parameters were fixed at μ = 0.05 and λ = 1 after it was experimentally found to produce the best segmentation output. The value of these parameters are set based on the lowest SSIM value as presented in Table 3. The algorithm was tested on water bodies with varied surface areas to validate its robustness, and it was found to yield satisfactory results. Fig 12 and Fig 13 presents the delineation output for two sample water bodies.

The usefulness of the developed algorithm in change detection studies has been investigated by applying the algorithms on multi-temporal Landsat data. Fig 14 presents the delineation output for Puzhal lake in India during two different years, 2018 and 2019.

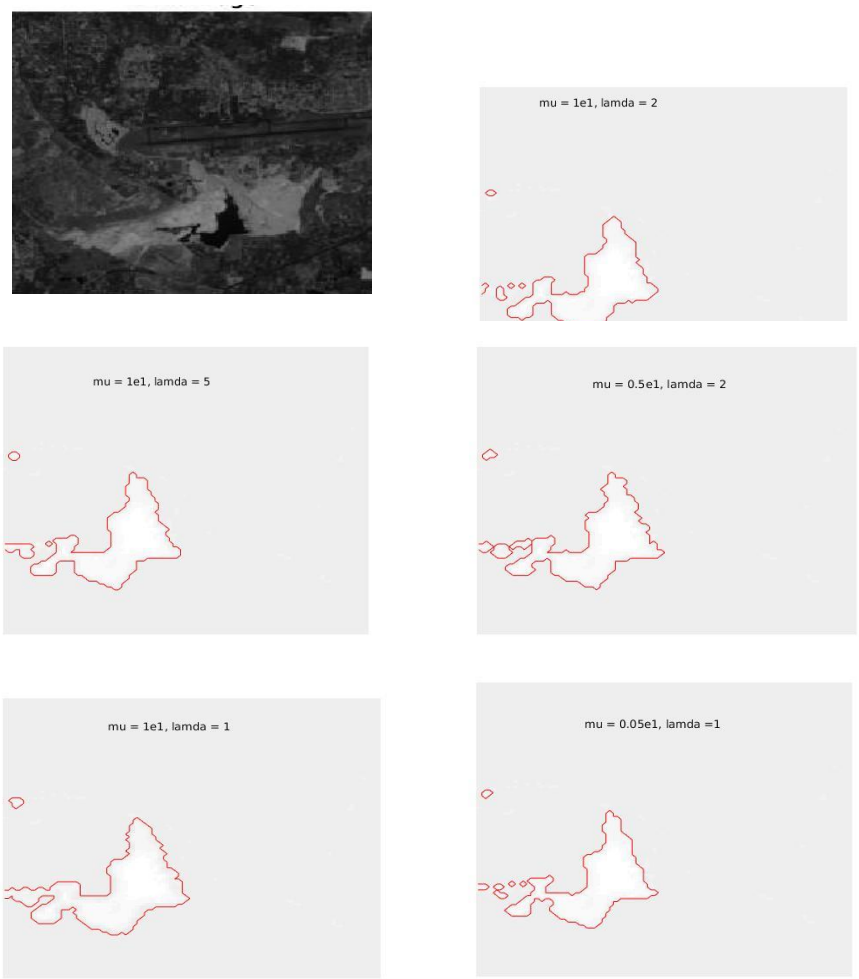

Fig 11: NIR band image of Bellandur lake, Bangalore and Segmentation Output variation according to different values of μ and λ

Table 3: Structural Similarity Index (SSIM) for different values of μ and λ

μ	λ	SSIM
1e2	1	0.2351
1e1	5	0.7041
1e1	2	0.8336
1e1	1	0.8465
0.5e1	5	0.9087
0.5e1	2	0.9312
0.5e1	1	0.9661

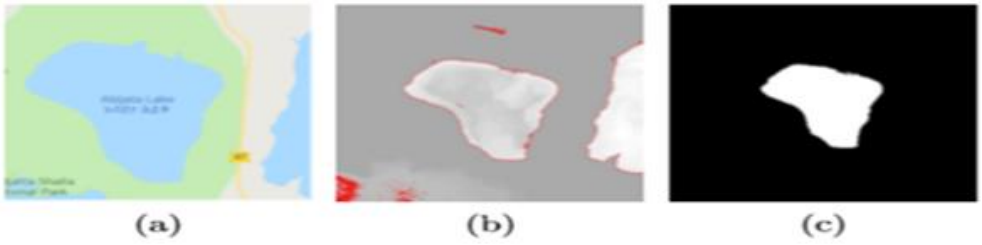

Fig 12: Segmentation Result for Lake Abijata, Ethiopia (a) Google maps image for visual reference. (b) Segmented image using proposed method. (c) Image after removal of unwanted region and binarization.

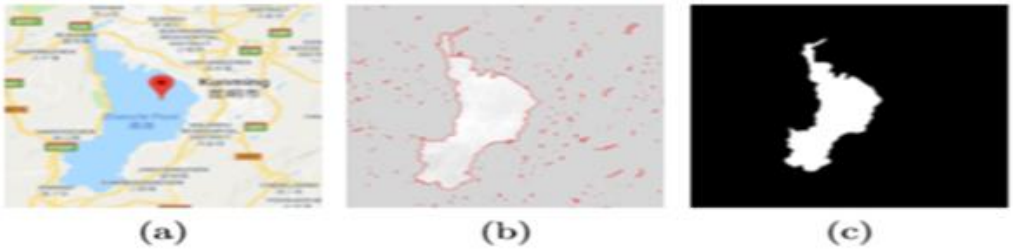

Fig 13: Segmentation Result for Lake Dianchi, China (a) Google maps image for visual reference. (b) Segmented image using proposed method. (c) Image after removal of unwanted region and binarization.

Quantitative validation of delineation accuracy was performed using Pearson's Correlation Co-efficient (PCC), Structural Similarity Index Measure (SSIM) and Dice similarity index. The proposed hybrid level set based water delineation was proved to outperform the established water delineation methods as summarized in Table 4. The accuracy of the proposed method was also compared with recent studies from the literature and was found to perform better as shown in Table

5. When compared to machine learning techniques that give comparable results, the presented level set algorithm is proven to be better as it is an unsupervised algorithm that executes faster and produces better delineation accuracy. The algorithm's performance was compared with and without the edge term to highlight the benefit of including the edge term in the formulation. The segmentation output with and without the edge term is shown in Fig 15 to 17. Figures 18 and 19 show the execution time and delineation output of various machine learning methods in comparison to the proposed work when applied to Bellandur Lake, Bangalore, India, which has a surface area of 3.61 km^2.

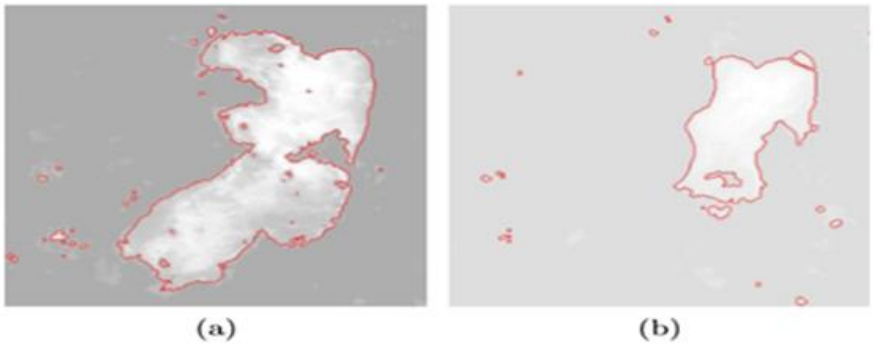

Fig 14: Segmentation Result for Lake Puzhal, Chennai, India. (a) In the year 2018 (b) In the year 2019

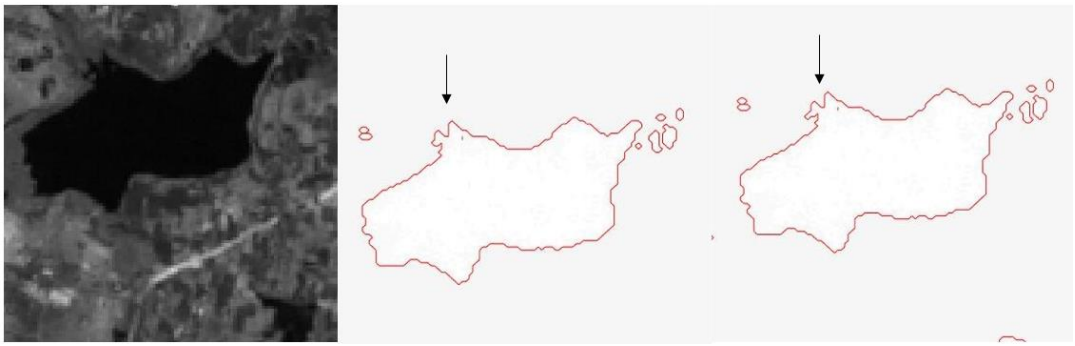

Fig 15: Delineation output with and without the edge term (a) NIR image of the study area (b) Delineation output without the edge term (c) Delineation output with the edge term [Bellandur lake]

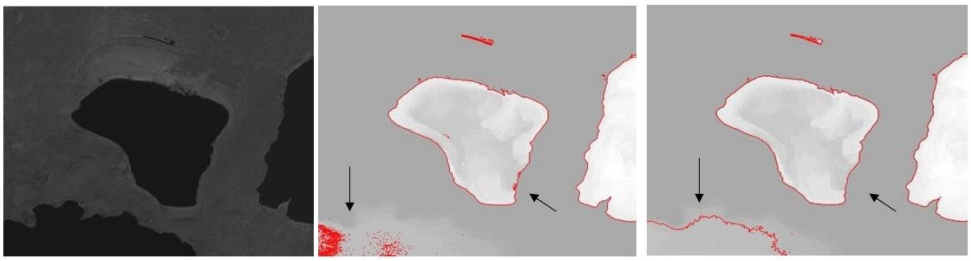

Fig 16: Delineation output with and without the edge term (a) Delineation output without the edge term (b) Delineation output with the edge term [Abijata Lake]

Fig 17: Delineation output with and without the edge term (a) Delineation output without the edge term (b) Delineation output with the edge term [Ulsoor Lake]

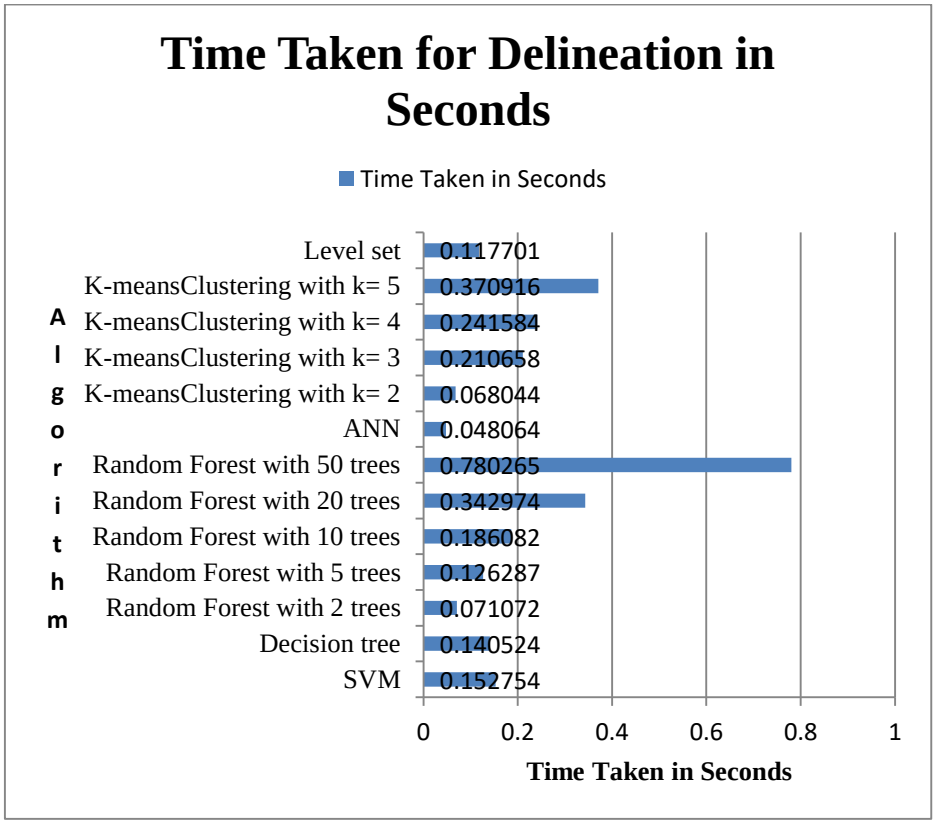

Fig 18: Execution time comparison of the proposed Level Set method with machine learning algorithms

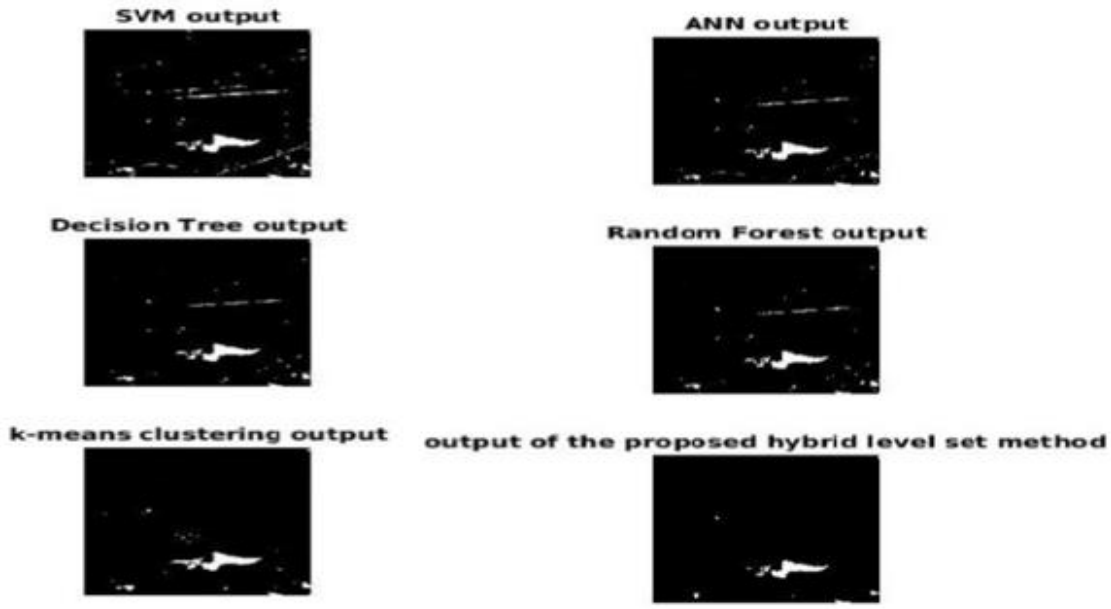

Fig 19: Comparison of delineation output of the proposed method with machine learning algorithms

Table 4: Comparison of the proposed delineation method with commonly used machine learning methods

	PCC	**SSIM**	**DICE**
Support Vector Machine	0.806	0.8626	0.8771
Artificial Neural Network	0.9328	0.8972	0.8995
Decision Tree	0.9415	0.9109	0.9317
Random Forest	0.9532	0.9118	0.9335
K-means Clustering	0.9501	0.9047	0.9258
Proposed Hybrid Level set	0.9772	0.9661	0.9611

Table 5: Delineation accuracy comparison with recent works in literature

Reference No.	**Authors**	**Year**	**Satellite (Spatial Resolution)**	**Accuracy %**
[19]	Évelyn M. Pôssa et al.	2018	Landsat (30m), Sentinel (10m)	86
[20]	Halder, T. et al.	2021	Sentinel (10m) *	97
[21]	W. Xue et al.	2021	GF3 (1m) *	98
[22]	Han, X. et al.	2021	Landsat (30m)	95
[23]	Zhang, L.et al.	2021	Landsat (30m)	95.5
Proposed Hybrid Level set based Surface Water Delineation algorithm	**Bijeesh TV, Narasimhamurthy KN**	**2021**	**Landsat (30m)**	**96**

After applying the hybrid level set algorithm to delineate the water body from the image, surface area computation is performed as per the formula given in the algorithm. The accuracy of the level set algorithm was also validated by comparing the computed surface area of nine water bodies with their actual surface area as presented in Table 6. The correlation co-efficient between the actual surface area and the computed surface area is 0.99.

Table 6: Delineation accuracy comparison with recent works in literature

Lake	**Computed Area using proposed method (km^2)**	**Actual Area (km^2)**	**Error**
Okaro	0.3	0.33	0.03
Okareko	3.15	3.3	0.15
Okataina	10.99	10.8	0.19
Rerewhakaaitu	5.01	5.8	0.79
Rotomahana	8.4	9	0.60
Tikitapu	1.11	1.5	0.39
Rotokakahi	4.01	4.5	0.49
Tarawera	40.03	41.7	1.67
Abijata	181.25	179.2	2.05

The water body delineation technique is then applied to Landsat multi-spectral data for the previous 25 years to track changes in water body surface area. The results of delineation employing the developed technique for lakes Bellandur and Varthur in Bangalore from 1987 to 2019 are shown in Fig 20 and Fig 21, respectively.

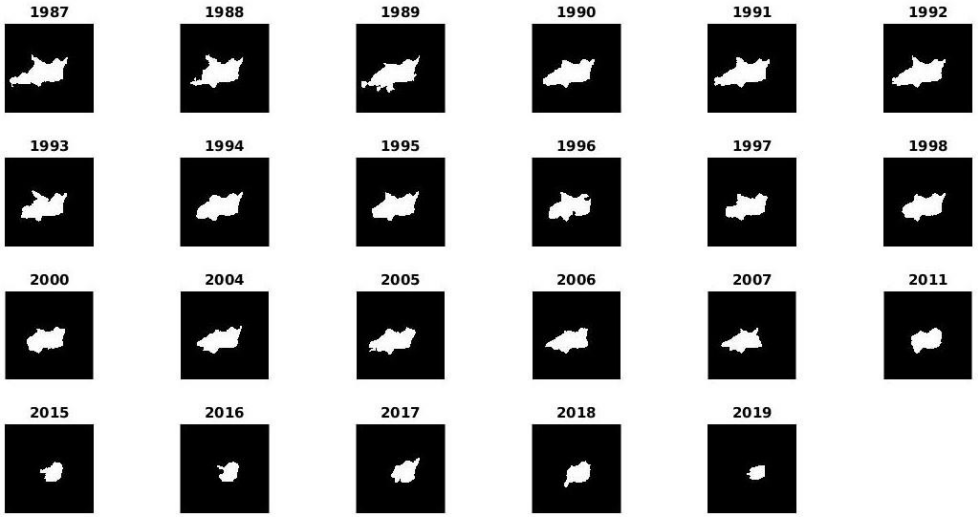

Fig. 20. Delineation output for Bellandur lake from the year 1989 to the year 2019.

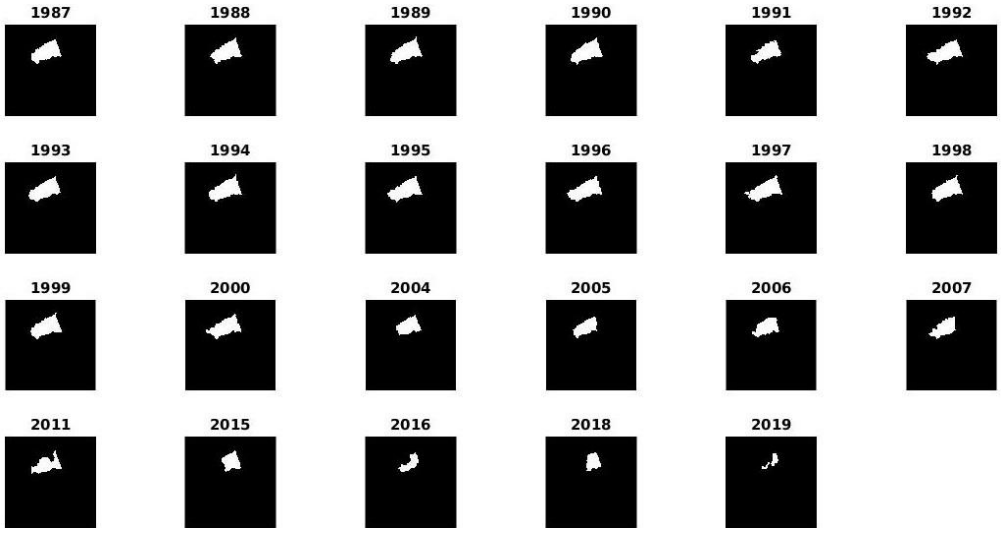

Fig. 21. Delineation output for Varthur lake from the year 1989 to the year 2019

The effectiveness of single exponential smoothing (SES) and double exponential smoothing models in forecasting the surface area of the delineated water bodies over the chosen time period was compared. Double exponential smoothing (DES)model takes the trend in the data into account and requires us to tune two parameters alpha and gamma. DES model gave optimum smoothing

for alpha = 0.94 and gamma = 0.5. The smoothing function for different values of alpha and gamma are shown in Fig 22 and the mean square error plot against alpha and gamma is shown in Fig 23. DES demonstrated good fitting on the data for the chosen values of alpha and gamma and thus DES is used in our surface area forecasting model.

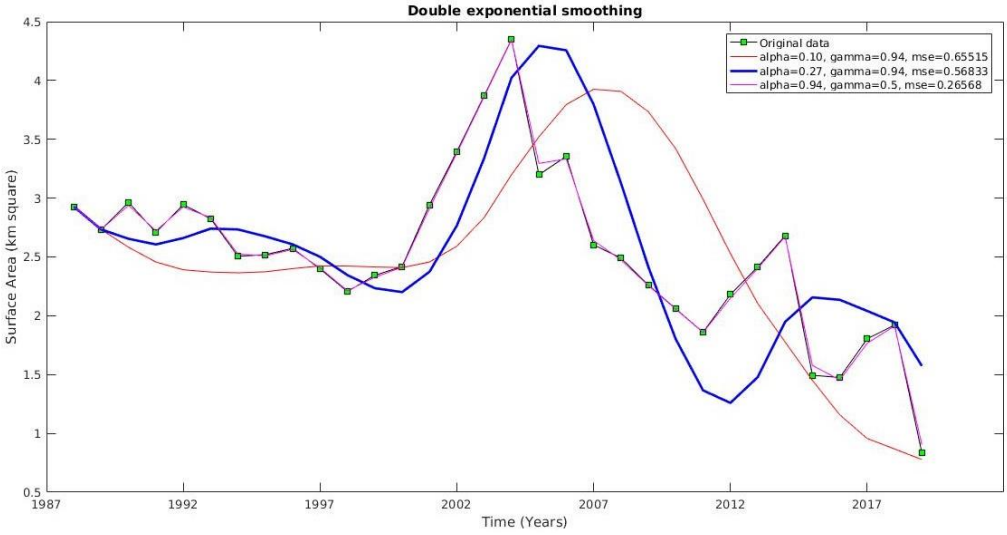

Fig 22: Double Exponential Smoothing function with different values of alpha and gamma

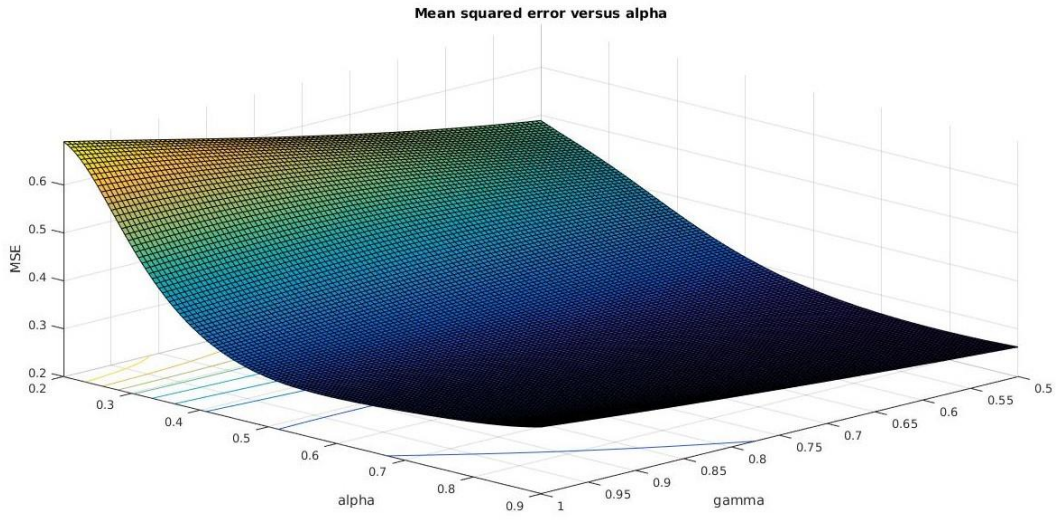

Fig 23: Error plot for Double Exponential Smoothing

The proposed forecast model does not account for any of the external parameters that might influence the change in the surface area of the water bodies. The experiments conducted could not establish any correlation between the surface area and external climate related parameters like average annual rainfall, average annual temperature and average wind speed. Thus it is justified to

formulate the problem as a univariate forecasting problem and use DES for the smoothing and forecasting.

Surface area data for nine lakes in Bangalore from the year 1987 to 2019 has been used in this study to establish the usefulness and effectiveness of the proposed generic forecasting framework. The proposed model was used to forecast the surface area for the year 2020 using the data up to 2019 and then used the actual surface area in 2020 to validate the accuracy of the model. The forecasting accuracy was measured using the average error and the correlation co-efficient between the actual area and the forecasted area. The average error was found to be 0.072 and the correlation co-efficient was computed as 0.94, which establishes the efficiency of the model in forecasting the future surface area from the past data on the surface area without considering any of the external factors which could potentially affect the surface area changes. Fig 24 and Fig 25 depicts how two sample lakes from the lakes under study have changed in surface area with respect to time and also shows the actual and the forecasted surface area for the lake in the year 2020.

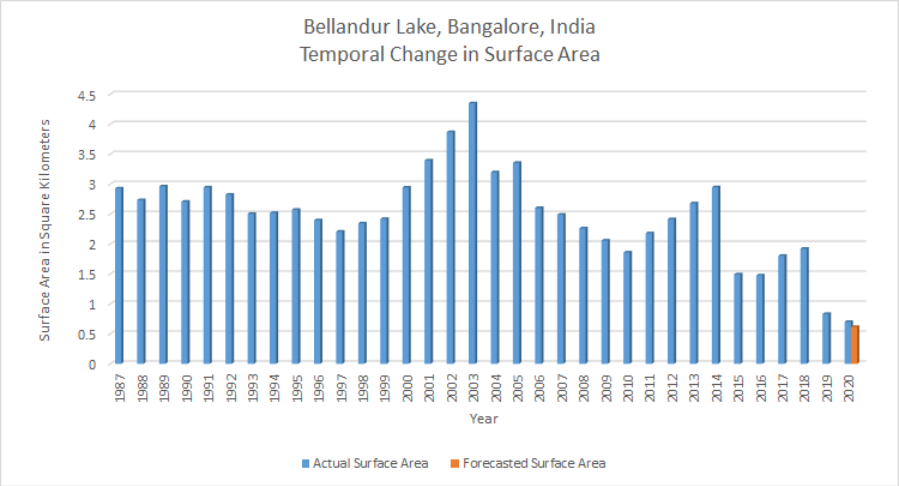

Fig 24: Surface Area Change Monitoring and Forecasting for Bellandur Lake

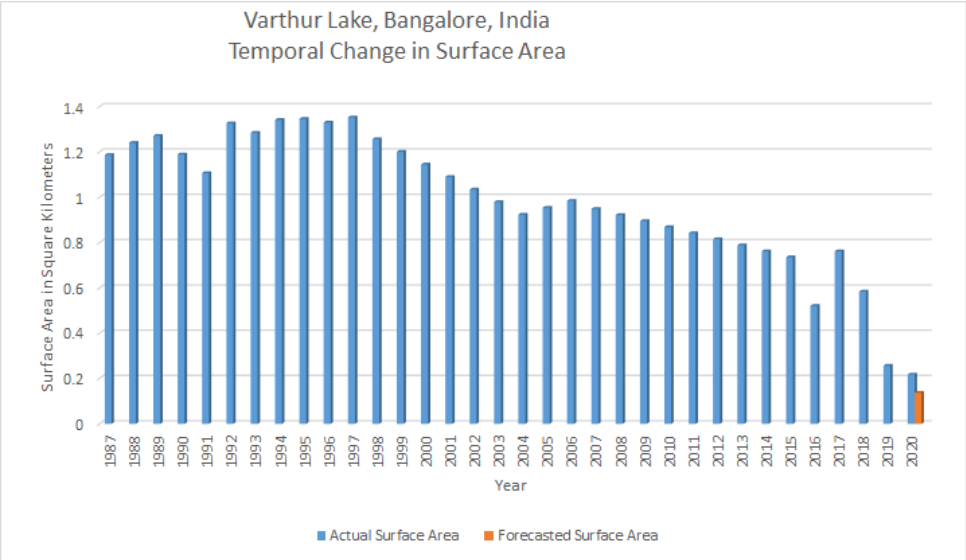

Fig 25: Surface Area Change Monitoring and Forecasting for Varthur Lake

Forecasting accuracy was computed based on the forecasted surface area for the chosen nine lakes. The accuracy was benchmarked using correlation co-efficient and average error and the proposed framework reported a correlation co-efficient of 0.94 and and the error margin was also acceptable as reported in Table 7.

Table 7: Surface area computation accuracy

Lake	**Actual Surface Area in 2020**	**Forecasted Surface Area for 2020**	**Error**
Bellandur Lake	0.701	0.6161	0.0849
Varthur Lake	0.2178	0.1375	0.0803
Ulsoor Lake	0.3753	0.3523	0.023
Madiwala Lake	0.7398	0.5353	0.2045
Jakkur Lake	0.3456	0.4419	0.0963
Doddenakkundi Lake	0.0648	0.0327	0.0321
Yele Mallappa Shetty Lake	0.8289	0.8796	0.0507
Muthanallur Lake	0.3438	0.3712	0.0274
Gottigere Lake	0.1863	0.2356	0.0493

The proposed framework was successfully used in forecasting the surface area of lakes in Bangalore using the past 30 years' data. The study could not establish any correlation between how the surface area of different lakes have been changing over the years. Specific customized study has to be conducted for each lake separately if the actual causes of the changes have to be understood. This framework can act as the tool for such study and the model can accommodate external parameters if a specific external factor is found to influence a specific lake under study. There could be many factors for the absence of a pattern in the changes to the lakes like the strategy adopted by the local administration and level or urbanization around it. For example, Ulsoor lake has sustained in its surface area without much depletion as its maintenance has been undertaken by the Madras Engineering Group of the Indian military for the past decade. On the other hand, lakes like Bellandur and Varthur have lost more than 75% of its surface area owing to pollution, mismanagement and illegal encroachment. This generic framework can be used by the local administrations to study and analyse the changes in surface area to the lakes under their jurisdiction and device specific strategies to rejuvenate of at least to make sure that no further damage is inflicted upon the lakes.

6. CONCLUSION AND FUTURE WORK

A generic framework for surface water delineation and change forecasting has been designed and developed using a hybrid level set based water body delineation algorithm and double exponential smoothing based forecasting on Landsat multi-spectral multi-temporal data. The framework consists of an effective pre-processing algorithm based on MNDWI, a hybrid level set theory based water delineation algorithm and a double exponential smoothing based forecasting model. The proposed hybrid level set employed the combination of edge based and region based level sets to account for both the local and global features in the image to improve the delineation accuracy. The hybrid level set algorithm was proven to outperform established water delineation algorithms. It was also established that the algorithm can be used for change detection studies by applying the algorithm to multi-temporal data. The hybrid level set based delineation was applied on multi-temporal Landsat multispectral images of water bodies in Bangalore in combination with a double exponential smoothing model to monitor and forecast the changes happened to the water bodies in terms of surface area. The proposed framework has demonstrated acceptable accuracy with minimal error and a correlation co-efficient of 0.94. The forecasting model uses a univariate smoothing model as no correlation could be established between the changes in surface area and external parameters like average annual rainfall, average temperature and average wind speed. The study also explored the possibility of patterns or correlation in the surface area changes of the selected lakes and found none. This points to the need for specific research to be done for individual water bodies to understand the causes for the changes and to device strategies to mitigate the depletion.

The proposed generic framework could be customized with external parameters to perform specific studies on selected water bodies. The framework could also be extended to perform water quality studies if a spectral library can be created for various types of water which can be used to train a machine learning model. The framework can also be improved by using images from multiple sources and fusing them to obtain better resolution images thereby giving improved results and better insights.

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PUBLICATIONS AND PROCEEDINGS

I. In Journals

1. “Water Body Change Monitoring and Forecasting using Double Exponential Smoothing Model on Multi-temporal Landsat data”, *Engineering Letters* (Scopus, ESCI) – Accepted for publication (2022)
2. TV, Bijeesh, and Narasimhamurthy KN. "A Hybrid Level Set Based Approach for Surface Water Delineation using Landsat-8 Multispectral Images." *Engineering Letters*, vol. 29, no. 2, 2021.
3. Bijeesh, T. V., and K. N. Narasimhamurthy. "Surface water detection and delineation using remote sensing images: a review of methods and algorithms." *Sustainable Water Resources Management*, vol. 6, no. 4, pp. 1-23, 2020.
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II. In IEEEXplore/Conferences/Symposia

1. Tv, Bijeesh, and Narasimhamurthy Kn. "A Comparative Study of Spectral Indices for Surface Water Delineation Using Landsat 8 Images." *2019 International Conference on Data Science and Communication (IconDSC)*. IEEE, pp. 1-5, 2019.
2. Bijeesh, T. V., and K. N. Narasimhamurthy. "A Generic Framework for Change Detection on Surface Water Bodies Using Landsat Time Series Data." *Computational Vision and Bio-Inspired Computing*. Springer, Singapore, pp. 303-314, 2021.